Multimarket Contact in Italian Retail Banking: Competition and Welfare

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Abstract

This paper studies banks' competitive behavior on the deposit side of the Italian retail banking industry. We use a structural model to estimate demand for deposit services and test several supply models. We find that both the competitive, differentiated product Bertrand and the perfectly collusive models are rejected against partially collusive models with coalitions based on the participants' market contact. In the best fitting collusive model, the coalition includes 8 banks with at least 19 overlapped regions. Banks with extensive multi-market contacts tend to be less competitive and behave as if they were maximizing their profit jointly, taking into account the competitive fringe of smaller banks.

Key words: Competition, multi-market contacts, retail banking, welfare analysis

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1 Introduction

Economists are divided on the issue whether banking competition is valuable and benefits consumers or whether it is harmful and pushes banks into excessively risky activities. This theoretical debate has gained even more importance after the recent banking crises. To test these theories empirically, however, one must first identify the level of competition in the banking sector. Reduced form, non-structural models (conjectural variation, Panzar-Rosse test) all have their problems[1] and cannot identify reliably the level of competition. Moreover, these methodologies are not useful to test policy and welfare implications because the reduced form parameters change with policy (as the Lucas critique suggests.)

This paper studies the competitive behavior in the Italian retail banking industry, using a structural model of demand and supply sides of the deposit market. We focus on competition in net interest rates and branching across all regions and use a non-nested test to identify the model that describes best the Italian banks' conduct. Besides the standard competition with differentiated products and perfect collusion models, we also consider partially collusive models based on the degree of bank size and multi-market contact.

Previous structural banking papers typically assume that banks compete in a differentiated product market by choosing interest rates given their number of branches and other characteristics. Dick (2008) is the first paper to estimate a nested logit model[2] for retail deposit services using data on U.S. commercial banks. She derives consumer welfare but does not test market power[3]. A different set of papers use structural demand models to test for market power in the banking industry. Ho (2008), Molnar (2008), Molnar et al. (2007) and Nakane et al. (2006) employ similar techniques to estimate not only demand but also market power on the supply side in the Chinese, Finnish, Hungarian and Brazilian retail banking, both on the deposit and on the loan side. These papers focus on short term, static competition and infer the form of the strategic conduct from the estimated own and cross-price elasticities and the marginal costs estimates.

Our paper, in line with the literature, combines the structural demand and supply models. Our main contributions, however, relative to the previous papers are that we employ non-nested tests (as in Gasmi et al., 1992) for the market power on the Italian retail deposit market and we consider not only the two extremes, a competitive and a perfectly collusive model of the supply, but also partially collusive models where the collusive groups are formed based on the number of deposit market coverage or overlap. We model partial collusion as a perfectly collusive cartel with a competitive fringe and use pairwise tests to examine which model fits the data best. Of course the number of

[1] See for example Reiss and Wolak (2005).

[2] Developed by Berry (1994).

[3] Since Dick, a few more papers applied the discrete-choice demand framework (nested or random coefficient logit) to analyze different questions in banking including Adams et al. (2007), Grzelonska (2005), Ishii (2005), Knittel and Stango (2008), Zhou (2008), all use U.S. demand deposits data.

theoretically possible collusive arrangements is very large due to the large number of banks so we need to limit the number of models we consider. We test collusive models based on multi-market contact, and deposit weighted multi-market contact. Multi-market contact is one of those factors which can facilitate and sustain implicit collusion as it was shown by Bernheim and Whinston (1990)[4]. For example, a potential partial (tacit or explicit, empirically not distinguishable,) collusion may be composed of banks with coverage or overlap on more than two markets. We test these partial cartels (that includes banks with similar market overlap) against each other, against the perfect cartel and Nash-Bertrand competition.

The existing empirical studies that relate the level of collusion and rivalry directly to multi-market contact mostly find that multi-market contact increases prices and profitability, and decreases competition (e.g. Parker and Röller (1997) in mobile phones, Leheyda (2008) in the auto industry). Davis and Huse (2010) and Sabbatini (2006) adopt a different approach to evaluate coordination in merger simulations. They consider tacit collusion with a grim-trigger punishment strategy and one extension is to examine the impact of multi-market contact. By contrast, we do not specify the punishment path. We implicitly assume that the punishment is monotonically related to the market coverage or multi-market contact. That is cartels that feature more multi-market contacts are more stable due to the increased ability to punish those agents that deviate from the collusive (implicit or explicit) agreement.

In reduced form models, De Bonis and Ferrando (2000) and Coccorese and Pellecchia (2009) studied multi-market contact in the Italian banking industry. Both studies use more disaggregated level data (Italian province level) than in our study (Italian region level.) De Bonis and Ferrando (2000) find that geographical overlap in banking is positively correlated with changes in market shares and lower lending rates, confirming the hypothesis of an overall increase in competition within the Italian banking system in the nineties. Coccorese and Pellecchia (2009) find that in the period 2002–2005 profitability is positively related to the average number of contacts among banks, and appear to be higher for those credit institutions experiencing more links. They conclude that the increasing consolidation (and hence the growing number of interactions in local markets) that has characterized this sector in those years were harmful for consumers and decreased competition in the Italian banking industry.

Similarly to Coccorese and Pellecchia (2009), we find that banks with an extensive multi-market contacts (at least 19 out of the 20 local markets) tend to be less competitive, pay lower deposit rates and behave as if they were maximizing their profit jointly taking into account the competitive fringe of smaller banks. We also estimate the welfare implication of this less than competitive behavior. In general we find that in the majority of the regions, the depositors' welfare per euro deposit decreased

[4] Their main idea is that when firms compete in multiple markets, they can punish deviation from tacit collusion more severely in all markets. As a result, in some circumstances, tacit collusion may be sustainable in markets where it otherwise would not be if firms did not have multi-market contact.

from 2003 to 2007, but the total consumer welfare increased due to the increased market size (financial assets) amounts. The depositors' welfare increased by about 10.5 billion euro or by 2.63 billions per year. In 2007, however, depositors' welfare would have been higher by about 1.80 billion euro if the banking sector were more competitive on the deposit services market. It is equivalent of a 13 basis point difference between the net deposit rates under the two alternative scenarios although the net deposit rate is not the only component of the depositors' welfare.

While the depositors' welfare seems to be higher under the counterfactual scenario our model need to be further extended to explore policy implications. Our paper provides a better approach to measure the competitiveness of the banking sector but it does not take into account the multi-product feature of the banking industry (most importantly the loan market and the potential cross-subsidization between different products) and does not take into account the potential trade-off between competition and stability of the banking system. Further research is necessary to include risk-taking into our model to enable us to draw firm policy conclusions.

The rest of the paper is organized as follows. Section 2 describes the Italian banking industry. Section 3 discusses describes the building blocks of the structural model. Section 4 presents the estimation strategy along with the identifying assumptions and the data. Section 5 presents the results of the estimation and robustness checks. Finally, section 6 provides conclusion.

2 Italian banking sector

2.1 Background

During the last 20 years, Italian banking has gone through a process of consolidation common to all European banking systems. Although this process has led to a sharp improvement of the sector's efficiency, banks have reacted to the sharper competition by cutting costs and expanding in size, often by merging with competitors. While the 1990s experienced a large number of mergers creating a few large regional institutions, as well as national banks, smaller local banks still dominate local deposit markets. These consolidations decreased the number of banking institutions but the deregulation of branching activities almost doubled the number of bank branches. The number of Italian banks decreased from 1064 in 1990 to 788 in 2009 while the number of branches increased from 17,721 to 34,036 respectively. At the end of 2009 the average number of inhabitants per branch is 1,610 nationally (1,320 in the Centre and North and 2,690 in the South.) 25 banks listed on the stock exchange; and the listed banking groups account for 64.3 per cent of Italian banks' assets. As documented in Cerasi et al. (2000), as a result of reforms on entry and branching regulation, the cost of branching in Italy has decreased significantly.

The mergers and acquisitions of the last decade have led to an increase in the degree of concentration of the banking system nationwide: between 2000 and 2009, the Herfindahl-Hirschman Index

(HHI), calculated on the total assets of the units operating in Italy, increased from 600 to 760 (on a scale of 10,000). However, in the same period the degree of concentration of local credit markets decreased. The average number of banks per province rose from 25 to 27. About 90 percent of the Italian population can choose from among at least three banks in their town of residence.

The two major groups (UniCredit and Intesa Sanpaolo) hold 33.9 per cent of the banking system's assets in Italy, while the other three medium-sized/large groups (Banca Monte dei Paschi di Siena, Banco Popolare and Unione di Banche Italiane) account for 18.6 per cent. A third category comprises 51 medium-sized/ small groups and stand-alone banks (including specialized banks and subsidiaries of foreign banking groups), with 35 per cent of total assets; the remaining 12.5 per cent is held by 590 small intermediaries with prevalently local operations (Bank of Italy, 2010).

Between 1990 and 2004 a total of 620 M&As were recorded, involving more than half of the total assets of the Italian banking system. The overall impact of these developments – deregulation and consolidation – on bank competition is a priori ambiguous. The existing academic literature has in general indicated that competition among European banks has increased only modestly as a result of deregulation. The Italian liberalization experience, on the other hand, suggests a stronger impact of barrier-to-entry removal in shaping a competitive banking sector environment (e.g. Angelini and Cetorelli (2003), Cetorelli and Violi (2005), and Focarelli and Panetta (2003)). Cost-price estimates suggest that M&As operations have improved banks' efficiency, and that such improvements have at least in part been passed on to banks' customers.

The Italian Competition Authority (ICA) launched several inquiries (i.e in 2006 and 2011) to determine the kinds and the extent of the user charges applied to banking services. They investigated current accounts, deposit services (such as bills of exchange and standing orders), and payment services (transfers, bancomat and pre-paid bancomat). According to the ICA, various complaints and a number of studies by foreign institutions (such as a European Commission study (2006)), consumer associations and consultants have highlighted the existence of high prices for banking services in Italy. This may indicate weak competitive forces in the market, to the detriment of consumers.

2.2 Data and Market Definition

We obtained our data from four main sources. Interest rates and the value of outstanding deposits come from the Central Credit Register (CCR) and Banks' balance sheet and income statement information come from the Banking Supervision Register (BSR). Both registers are managed by the Bank of Italy. Interest rate data classification and compilation criteria are harmonized according to the European Central Bank (ECB) statistical reporting system for Monetary Financial Institutions (MFI). The Central Credit Register is a department of the Banca d'Italia that collects data on the interest rates above a certain threshold. The Banking Supervision Register also provides the data on the deposits of individual banks in each region, with a breakdown by size of the deposit and type of depositor. Finally, we supplement these data with region-specific indicators, such as the number of new banks entering each local market.

We define the geographic market as a region in Italy, totally 20 regions. In dealing with merger cases, the Italian Competition Authority considers the province as the relevant geographic market, as far as the market for deposits were to be concerned; with regards to loans, the relevant market is considered to be the region. It would be ideal that we define the geographic market as a province. Unfortunately, the regional level was the finest geographic data that we could get access to. Our choice has been driven by data availability but one can also argue that in recent years the structural changes within the banking sector (deregulation, online banking higher customer mobility, technological progress) could have widened the boundaries of the relevant geographic market also for deposit services. Moreover, since we do not have regional variation in the interest rates, the market definition probably has no impact on the estimated interest rate elasticities.

The total market is defined as the total financial assets.[5] The inside market shares are defined on the basis of euro deposit data collected at each bank in each region in Italy.

The sample is from 2003 to 2007. We drop observations with missing variables or average service rate greater than 10% or banks with deposits in a region less than $10,000$ Euros. Table 1 presents the summary of statistics on the bank-year level, bank-region-year level, and market level. The data cover 5 years, 20 regions, and 105, $104, 103, 103, 102$ banks in years 2003 to 2007 respectively. The average (median) number of banks per market is about 31 (28.5). The market shares show that the Italian banking system is still rather fragmented with numerous small banks. (The mean within market share is 3.2%.)

3 Model

We consider a structural model of demand and supply of retail deposit services. We think of retails banks as service providers that are differentiated in terms of observed and unobserved (by the econometrician) characteristics such as observed interest rates, service fees, number of branches versus unobserved reputation, bundling of products, advertising etc. In the baseline model, on the demand side we use the specification of Dick (2008) and assume that consumers are interested in purchasing deposit services from a single bank. Similarly to Dick (2008), data limitations drive a number of modelling choices, but seems unlikely to significantly affect the interpretation of the results.

Following Berry (1994), from individual consumer utility maximization one can aggregate and relate an aggregate market share as a function of observed and unobserved product characteristics. We use instruments for the endogenous prices (in this application net deposit interest rates), the

[5] The data are from the Bank of Italy's survey on income and wealth which has a regional breakdown of real and financial assets held by Italian household. For robustness check we have also explored two other total market definitions such as total wealth of households that included also real assets and the total deposits in all monetary institution.

number of branches within regions and for the nest shares in the demand estimation.

On the supply side we consider deposit-taking retail banks, which are primarily used to generate revenue through the funding of various credit instruments. These banks are therefore multiproduct firms; however, this paper focuses only on the deposit side of the banking industry and does not explicitly model any decisions on the lending side. We assume that each bank chooses a single net price (service fees - interest rates on deposits) to maximize its total profits over the whole country conditional on their and their rivals' characteristics (branch network size, age, number of regions they operate) and the deposit return rate. The deposit return rate, defined as the return that each bank can achieve on the deposit amounts by lending etc., depends on the bank characteristics and year-bank dummies. Even though the banks charge national interest rates, deposit return rates could vary region-by-region due to the different product-mix and costs.

3.1 Demand Side

Following the tradition of differentiated products demand models, we derive the demand function from individual utility maximizations with discrete choices. In our model, each consumer decides about savings and then chooses a single commercial bank for depository services or chooses the outside option of not keeping his or her money in a commercial bank. We treat each bank as a single product firm offering deposit services. Assume that $m = 1, ..., MT$ markets are observed, each with $i = 1, ..., I_m$ consumers and $j = 1, ..., J_m$ banks. We adopt the several nested logit models to estimate the demand function. In our baseline specification we assume that consumers first make a decision on whether to save or not and then they choose their bank. Hence all inside products (the individual commercial banks) combined into one group and the outside option into another. In an other specification, we have collected national and regional banks in separate nests. Section 5.1 will provide a more detailed description of the demand specifications and the estimation results. The outside goods are all the other financial assets excluding bank deposits.

The logit and nested logit specifications averages over the individual-specific variables first and then uses these averaged variables to calculate the choice probabilities of a market-level representative agent. This is clearly a restrictive assumption, however, our more general, random coefficient model was unable to capture consumer heterogeneity and we found that the nested logit specification fitted the data better.

The conditional indirect utility function of consumer i for choosing bank j's deposit services in market m (region-year) takes the following form:

$$
\begin{aligned}
u_{ijm} &= \alpha(-p_{jm}) + x_{jm}\beta + \xi_{jm} + \xi_{ig} + (1-\sigma)\epsilon_{ijm} \\
&= -\alpha p_j + \beta_n \ln(n_{jm}) + \beta_r \ln(regions_j) + \beta_a d\_age_j \\
&\quad +\xi_{jm} + \xi_{ig} + (1-\sigma)\epsilon_{ijm},
\end{aligned} \tag{1}
$$

where $-p_{jm}$ is the average net deposit interest rate (the average deposit interest rate minus the average service rate), n_{jm} is the number of bank j's branches in market m, $regions_j$ is the number of regions that bank j has presence, d_age_j is an age dummy of bank j (1 if the age is no less than 15 years)[6], ξ_{jm} is unobserved product quality, ξ_{ig} consumer i's utility, common to all products belonging to group g, ε_{ijm} is the consumer-specific deviation from mean utility, and α, β_n, β_r, β_a, and σ are demand parameters to be estimated. We also include fixed effects for regions and years. The ε_{ijm} is assumed to be a mean zero stochastic term with i.i.d. extreme value Type 1 distribution.

As Berry (1994) shows, under these assumptions it is possible to aggregate the individual choices and derive the equation to estimate the nested logit model:

$$
\ln(s_{jm}) - \ln(s_{0m}) = -\alpha p_{jm} + x_{jm}\beta + \sigma_g \ln(s_{j/gm}) + \xi_{jm}, \tag{2}
$$

where s_{0m} is the market share of the outside good and is defined by $s_{0m} = 1 - \sum_{j=1}^{J_m} s_{jm}$, and $s_{j/gm}$ is the within group market share and is defined by $s_{j/gm} = s_j / \sum_{j=1}^{J_m} s_{jm}$. This term is also endogenous together with the prices and instrumental variables are necessary to obtain consistent estimates.

The equation can be estimated by treating the unobserved product quality (ξ_{jm}) as an unobserved error term. The bank-specific unobservable, ξ_{jm}, accounts for the various aspects of bank quality that are unobserved or otherwise omitted. This may include advertising and promotion activity of the bank, the variety of account offerings, and the quality of customer service training. These unobserved characteristics could correlate with the endogenous characteristics (for example service quality could negatively correlate with net deposit rates) and cause a simple OLS estimation to be biased. We assume that the number of regions and the age of the banks are exogenous characteristics while the number of branches and the net deposit interest rates are endogenous. We will control for this endogeneity problem by using instruments.

In the long run, the number of regions where a bank is present is most likely also endogenous. Our data and our model, however, focuses on the medium run. Opening a branch in a region where a bank has not been present requires a much higher investment in, for example, advertising and takes more time than increasing the number of branches in regions where the bank is already present and known by the population. We include both the number of regions and the branches (measured in

[6] The age is defined as the number of years since the creation of the bank, but if a bank is older than 15 years, then the age variable is assigned as 15 in our data. Hence, we introduce the age dummy variable.

logarithms) to capture their declining effect on demand for deposits. Finally, we add region and year dummy variables to capture the effects of changing macroeconomic conditions in a given region and a given year.

3.2 Supply Side

On the supply side we consider different models of oligopolistic competition. Our models are versions of the Monti-Klein model of banking with product differentiation and collusion. Banks are multi-product firms. They provide deposit services for savers (i.e. take in deposits), which they primarily use to generate revenue through the funding of various credit instruments. We assume that banks maximize their joint profit of all sub-markets (i.e. deposit, loan and other product markets) and that the interbank market is perfectly competitive (i.e. banks can freely loan or borrow the excess or necessary funds from the market at a fixed interest rate[7]). This paper, however, focuses on the deposit side of the banking industry and does not explicitly model any decisions on the lending side.

In the competitive model, given consumer preferences and costs of all banks, bank j chooses its net deposit interest rates and the number of branches in each regions to maximize its profit in each time period.

In the perfectly collusive model, given consumer preferences and costs of all banks, bank j chooses its prices and the number of its branches to maximize the joint profits of all banks. In a collusive equilibrium the profit-maximizing banks internalize the negative business stealing effect they have on other banks and therefore charge a higher price (lower interest rates or higher service fees in the case of deposits).

In the partially collusive (implicit or explicit, observationally equivalent) models, depending on the number of multi-market contacts, the colluding banks maximize the joint profit of the colluding group.

3.2.1 Profit maximization under different conducts

Given consumer preferences and characteristics of all banks, bank j chooses its price in each market m to maximize the following expression,

$$\begin{aligned} & \max_{p_{jm}} \pi_{jm} + \sum_{k \neq j} \lambda_{jk} \pi_{km} \\ = \quad & (r_{jm} + p_{jm}) M_m s_{jm} + \sum_{k \neq j} \lambda_{jk} (r_{km} + p_{km}) M_m s_{km}, \end{aligned}$$

[7] This assumption guarantees that the profit maximizing decisions are independent in the separate markets. The assumption seemed to be innocuous before the banking crisis. As recent events showed in practice it is not necessarily true.

where different values of $\{\lambda_{jk}\}_{j,k}$ stands for different competition patterns, $\lambda_{jj} = 1$ for $\forall j$, r_{jm} is the deposit return rate that we will estimate, it includes non-interest marginal cost and the loan or interbank interest rates, M_m is market size of deposits in market m, and s_{jm} is the market share of bank j on market m,if bank j does not have any deposits on market m, then s_{jm} is 0.

The first-order condition with respect to p_{jm},

$$M_m s_{jm} + \sum_{k \neq j} \lambda_{jk}(r_{km} + p_{km}) M_m \frac{\partial s_{km}}{\partial p_{jm}} = 0. \tag{3}$$

We define $\frac{\partial s_{km}}{\partial p_{jm}} = 0$ if neither bank j nor k presents on market m.

Solve for interest rate, r,

$$r = -p - (\triangle^p)^{-1} \cdot s. \tag{4}$$

where Ms is a $J \times 1$ matrix, $\triangle^p$ is a $J \times J$ matrix with elements:

$$\triangle^p_{jk} = \lambda_{jk} \frac{\partial s_{km}}{\partial p_{jm}}.$$

Different models of competition can be included in this framework depending on the values of λs.

If $\lambda_{jj} = 1$ for $\forall j$ and $\lambda_{jk} = 0$ for $\forall j \neq k$, then banks are interested in maximizing only their own profit and we are in a Nash-Bertrand competition.

If $\lambda_{jk} = 1$ for $\forall j, k$, then the banks are interested in maximizing their profit jointly, i.e. all banks collude and we have a perfect collusion model.

If for a set of banks, J_c, $\lambda_{jk} = 1$ for $\forall j \in J_c$, $\lambda_{jj} = 1$ for $\forall j$, all other λ_{jk} are equal to 0, then banks J_c are partially colluding and maximizing their profit jointly given the competitive fringe. We select the set of colluding banks based on the number of their multi-market contact.

In a price-setting equilibrium, the profit-maximizing banks internalize the negative business stealing effect they impose on other banks and therefore charge a higher price (lower interest rates or higher service fees in case of deposits) as the degree of cooperation increases. In the empirical application we constrain the regional prices to be the same in that we do not observe interest rates variations at regional level in our data.

In theory, it is possible to directly estimate the λ matrix. These estimated parameters are equivalent to the conjectural variation parameters used in the literature for homogenous products. Nevo (1998) shows that in principle these parameters are identified. However, he also argues that "in practice, it is hard, if not impossible, to find such a large number of exogenous variables that influence demand but are uncorrelated with the shock in the pricing equation." Nevo (1998) concludes that "even for this relatively simple example there is little hope of identifying all the CV parameters in practice."[8]

[8] Further problems with the conjectural variation method are discussed by Corts (1999).

Similarly to Bresnahan (1987), we estimate several sets of demand and supply parameters under different modes of conduct corresponding to different values for the elements of the λ matrix, in accordance to the interpretation suggested by economic theory. Then we test between the different models of conduct by comparing the fit of the various models using the non-nested test of Rivers and Vuong (2002).

We instrument the number of branches in the demand estimation without explicitly modelling how these numbers are determined. The exercise of modelling branching decision is left for future research.

3.2.2 Deposit return rate

The deposit return rate summarizes the non-interest marginal cost and the loan or interbank interest rates that a specific bank can earn on the deposit amounts. Researchers have traditionally included product characteristics as determinants of marginal costs or estimated a translog cost function on accounting data. We follow the first approach and specify the deposit return rate of bank j as a function of the observed exogenous characteristics (number of regions where the banks operate, the age of the bank and whether it is a national bank (operating in more than 16 regions)):

$$r_{jm} = \gamma_0 + \gamma_r \ln(regions_j) + \gamma_a d\_age_j + \gamma_n d\_national_j + \omega_{jm}, \tag{5}$$

where

ω_{jm} is unobserved supply factors, and

γ_0, γ_r, γ_a, and γ_m are parameters to be estimated. We include year dummies and region dummies.

The deposit return rate is strongly related to the loan interest rate. However, the loan interest rate is an endogenous variable. The deposit return rate is assumed to be the outcome of the optimal loan rate for a given bank. Hence, we do not include the endogenous loan interest rate as a regressor in the specification above.

3.3 Elasticities

3.3.1 Local market elasticities

The implied own- and cross-price elasticities for the average deposit interest rates minus service fees in a local market m are:

$$\varepsilon_{jjm} = \frac{\partial s_{jm}}{\partial p_{jm}} \frac{p_{jm}}{s_{jm}} = -\frac{1}{1-\sigma} \alpha p_{jm} \left(1 - \sigma s_{j/gm} - (1-\sigma) s_{jm}\right), \tag{6}$$

$$\varepsilon_{jkm} = \frac{\partial s_{jm}}{\partial p_{km}} \frac{p_{km}}{s_{jm}} = \frac{1}{1-\sigma} \alpha p_k \left(\sigma s_{k/gm} + (1-\sigma) s_{km}\right) \text{ if } j \neq k \text{ and } k \in g, \tag{7}$$

where σ is the within group correlation of utility levels. These elasticities refer to the percentage change in market share in response to a change in net interest rates. The cross-price elasticity between product j and product k located in a different group g is independent of j.

Note that $-p_{jm}$ is the average deposit interest rate minus the service rate. Usually, the average deposit interest rate is greater than service fee (about 90%) or the price, p_{jm}, is negative. The own price elasticity is usually positive rather than negative.

3.3.2 Whole market elasticities

In Italy, at least in our data, the average deposit interest rates and service fees do not vary regionally. This fact could in itself indicate a less than competitive behavior although other cost-related factors could also provide an explanation. Any change in deposit interest rates and service fees, as they are nationally set, should have impact on every local market. We should also compute the whole market elasticities as well when examining the price elasticities.

The whole own- and cross-price elasticities for the average deposit interest rates minus service fees are:

$$\begin{aligned} \varepsilon_{jj} &= \frac{\partial TDep_j}{\partial p_j}\frac{p_j}{TDep_j} \\ &= (\sum_m M_m \frac{\partial s_{jm}}{\partial p_j})\frac{p_j}{\sum_m M_m s_{jm}} \\ &= [\sum_m M_m s_{jm}\frac{1}{1-\sigma}\alpha\left(1-\sigma s_{j/gm}-(1-\sigma)\, s_{jm}\right)]\frac{p_j}{\sum_m M_m s_{jm}}, \end{aligned} \tag{8}$$

$$\begin{aligned} \varepsilon_{jk} &= \frac{\partial TDep_j}{\partial p_k}\frac{p_k}{TDep_j} \\ &= (\sum_m M_m \frac{\partial s_{jm}}{\partial p_k})\frac{p_k}{\sum_m M_m s_{jm}} \\ &= -[\sum_m M_m s_{jm}\frac{1}{1-\sigma}\left(\sigma s_{k/gm}+(1-\sigma)\, s_{km}\right)]\frac{p_k}{\sum_m M_m s_{jm}}, \end{aligned} \tag{9}$$

where $TDep_j = \sum_m M_m s_{jm}$ stand for the total deposits of bank j across the whole country. These elasticities refer to the percentage change in market share in response to a change in price. The cross-price elasticity between product j and product k located in a different group g is independent of j. Note that the whole cross-price elasticity can be equal to 0 if banks j and k do not have any overlapped markets.

4 Estimation

For the demand side, we adopt a nested logit model. The simple logit model has the so-called independence of irrelevant alternatives property when only aggregate data are available and the estimated substitution patterns are very restrictive. The model implies that if two products have the same market share then they have the same cross-price elasticities and the same markups. The nested logit slightly improves this problem as these issues arises only within nests. Nonetheless, the logit and nested logit estimations are computationally less burdensome than that of the mixed logit model (BLP), and may also provide substantial intuition regarding the validity of the identification strategy. We also estimated a mixed logit model but we found that the random coefficient parameters were not significant and our nested logit specification performed better.

The net price and the number of branches of a bank in a region are endogenous variables and this fact calls for instrumental variables. We adopt Generalized Method of Moments (GMM) as estimation method similarly to Berry, Levinsohn and Pakes (BLP) (1995). Our moment conditions state that the cost and demand shocks, ω and ξ are independent of our instruments, i.e. they form the following moment conditions:

$$\begin{aligned} E[\xi|z^d] &= 0, \\ E[\omega|z^s] &= 0. \end{aligned}$$

Following BLP (1995), the set of instruments include exogenous characteristics of competitors and exogenous marginal cost shifters. We have computed the sum of competitors' characteristics and then averaged this sum across each bank's markets and use these as instrument.

For the supply side, we estimate the model under the 21 assumptions: (i) Nash-Bertrand, (ii-xx) partial collusion of the banks with market coverage $n(= 20, ..., 2)$, (xxi) perfect collusion. They are ordered by the decreasing degree of competition.

We estimate the demand and the supply models both separately, to avoid the contamination due to the misspecification of either the demand or the supply models, and jointly as well, to increase the efficiency of our estimates. In the joint estimation we allow for an arbitrary dependence between the cost shock ω and the demand shock ξ. We also allow for arbitrary correlations of ω and ξ among products within the same market.

4.1 Instruments

In our base specification, demand is affected by net interest rate, the logarithm of the number of branches, the logarithm of the number of regions where the bank is present, the age dummy of the banks (as proxy for reputation and relationship), the logarithm of the within group share and market and year dummies. The net interest rate, the within group share, and the number of branches are endogenous, so we used the instrumental variable technique.

Our instrumental variables include three parts. The first part consists of the exogenous bank characteristics (bank-year level), including the logarithm of the number of regions, the age dummy variable of a bank. The second part is constructed from the given bank characteristics, or BLP IVs (bank-region-year level), including the logarithm of the sum of the number of regions where all the other regional rival banks operate, the logarithm of the average of the number of regions where all the other banks have at least one branch, and the average age of all other rival banks (in logarithm). The third part is related to cost characteristics, including the ratio of total cost (including personnel cost) to total assets, the ratio of liquid assets to total assets, and the ratio of bad loans to total assets. The bad loans is at bank-region-year level, and total cost and liquid assets are both at bank-year level. These cost variables control for operating expenses, and affect the deposit interest rate. They are not supposed to be correlated with the demand shocks. Small depositors are covered by the deposit insurance and when they selects a bank, the depositors usually value the benefits from bank's services and interest rates rather than the strength of the its financial statement (where the cost variables reported).

Since the Rivers and Vuong (2002) test requires overidentification, we use two extra IVs on the supply side: the total number of regions where all the other regional rival banks operating, and its squared value (both measured in logarithm).

5 Empirical Results

Firstly, we present the separate and joint demand and supply parameter estimates under different supply models. Secondly, we test which supply model fits the data best. Finally we present some welfare estimates from a counter-factual simulations.

5.1 Demand and supply estimations

As discussed previously, for the demand side, we use a nested logit model.[9] We have estimated our demand model both separately and jointly with the supply models.

Table 2 present the first stage regressions of our base specification for the within nest share, the net deposit rate and for the number of branches, respectively. We use region and year dummies to help to control for the unobserved demand shifters. In the reported regressions, standard errors are clustered at the bank level. The instrumental variables mostly have significant explanatory power and the estimation satisfies the usual instrument test for relevance and validity. The Shea partial R^2 measure and the first stage F and Anderson statistics indicate that the hypothesis that our

[9] We also estimated a random coefficient logit model (see BLP (1995) and Nevo (2001)). Unfortunately none of our random coefficient are significant.

instruments are relevant cannot be rejected. The Hansen J-test indicates that the null hypothesis of correct model specification and valid overidentifying restrictions cannot be rejected.[10]

Table 3 presents the parameter estimates of the demand function and the results of the specification tests with the separately estimated demand. We use three nested logit model to estimate the demand. Models (i), (ii) put all banks into one nest. Model (iii) classifies banks into two nests: national banks and local banks, where the national banks are defined as banks with market coverage of at least 16 regions. The distribution of banks' market coverage is shown in Figure 1. Model (iv) is a two level nested logit model. First, we put all banks into one nest; Second, we further classify banks into two nests: national banks and local banks.[11] In Model (iv), the group segmentation parameter (σ_g) is negative and insignificant at at 5%. A t test shows that the subgroup segmentation parameter (σ_{kg}) is insignificantly different from the group segmentation parameter (σ_g) at 5% level (with t statistic equal to 1.547). This means that the two-level nested logit model can be reduced to either Model (ii) or Model (iii). In Tables 4, we summarize the elasticities of Models (ii) and (iii). The price elasticities for Models (ii) and (iii) are close. For example, the mean of local market own-price elasticities are 0.9276, 0.9524 for Models (ii), (iii) respectively.

We use model (ii) as our demand estimates in the following analysis for three main reasons. First, the R^2 of Model (ii) is greater than Model (iii). Second, the classification of national and regional banks is based on bank's coverage, which we have already included as an exogenous bank characteristic in the demand estimation. That is to say, Model (ii) has already taken whether a bank is national or regional into consideration. Third, a classic criticism to the nested logit model is that we might make some arbitrary standard to classify products into different nests. According to Figure 1, there is no clear break in the distribution of banks' coverage.

Most of the parameters are estimated with precision and they have the expected sign. Consumer utility (and the market share of the bank) is increasing in the net deposit interest rate and the number of branches. The parameter of the within group share indicates that our nested logit specification fits the data well and indeed the products in the nest are closer substitutes to each other than to the outside good. The number of regions where the bank is operating and the age dummy variable of the bank do not have significant effects on market shares.

For the supply side, the deposit return rate depends on the logarithm of the number of regions where the bank is operating, the age dummy, the national bank dummy, year dummy, and region dummies.

[10]These tests are part of the standard output of ivreg2 command in Stata and their detailed description can be found for example in Baum (2006.)

[11]The estimation regression equation for the two-level nested logit model is
$\ln(s_{jm}) - \ln(s_{0m}) = -\alpha p_j + x_{jm}\beta + \sigma_{kg}\ln(s_{j/gm}) + \sigma_g \ln(s_{g/Gm}) + \xi_{jm}$,
where $s_{j/gm}$ is the within group market share of bank j in its subgroup (national or local banks) in market m, and $s_{g/Gm}$ is the ratio the market share of national banks (if bank j is a national bank) or local banks (if bank j is a local bank) to the market share of all banks in market m.

For the supply side, we estimate the model under the following 21 assumptions: (i) Nash-Bertrand,

$$\lambda_{jk}^{Bert\,\mathrm{rand}} = \begin{cases} 1, & \text{if } j = k; \\ 0, & \text{otherwise.} \end{cases}$$

(ii-xx) collusion of the banks with market coverage $n(= 20, ..., 2)$ or CI n,

$$\lambda_{jk}^{CI\ n} = \begin{cases} 1, & \text{if } j = k; \\ 1, & \text{if market coverage of } j \geq n, \text{ and market coverage of } k \geq n; \\ 0, & \text{otherwise.} \end{cases}$$

(xxi) perfect collusion

$$\lambda_{jk}^{Collusion} = 1 \text{ for all } j, k.$$

Columns in Table 5 report the marginal cost parameters under six different supply side modeling assumptions.

The marginal cost parameters include a constant, the exogenous bank characteristics, year dummies, and region dummies. Our results indicate that older banks have significantly lower deposit returns. This fact could be due to either higher non-interest costs, lower loan interest rates or possibly stronger market power than younger banks due to long term relationships that they had more time to build. A national bank tend to have higher deposit returns, which is probably due to the fact that a national bank caters to different loan markets (i.e. credit cards vs mortgages) than regional banks. The sign of the number of regions where the bank is present changes with the supply model. It switches from significantly negative to insignificant as we consider more and more competitive supply models.

We have estimated demand and supply jointly as well. Both the estimated demand and supply parameters seem to be robust and do not change significantly under different supply models relative to the separately estimated parameters.[12]

5.2 Testing bank conducts

We use the Rivers and Vuong (2002) test for selection among the firm conducts. Table 6-A reports the non-nested test results from the estimates when demand and supply are estimated separately. The competition patterns are ordered from the most competitive one (Bertrand) to the least competitive one (collusion). In Table 6-A, the test statistics of -3.2843 shows that we can reject perfect collusion against the Nash-Bertrand competition at 1% significant level. The only model that cannot be rejected by any other and all others can be rejected against at 5% significant level is the one where

[12] We omit the results for saving space, however, these are available upon request.

banks with at least 19 regions form a coalition. In 2007, there are 8 banks with at least 19 market coverage.

For the robustness checks, we also consider a few other measures of multi-market contacts.

First, we checked a pairwise measure. Banks i and j cooperate (i.e $\lambda_{ij} = \lambda_{ji} = 1$) if the number of their overlapped markets is greater than n ($n \in [1, 20]$). If bank k overlaps with bank i on more than n market but does not overlap with bank j the corresponding lambdas would be $\lambda_{ik} = \lambda_{ki} = 1$ but $\lambda_{kj} = \lambda_{jk} = 0$. The corresponding values of λs for collusion of the banks with the number of overlapped market $\geq n (= 1, ..., 20)$ or CII n, are

$$\lambda_{jk}^{CII\ n} = \begin{cases} 1, & \text{if } j = k; \\ 1, & \text{if the number of overlapped markets of } j \text{ and } k \geq n; \\ 0, & \text{otherwise.} \end{cases}$$

The second measure takes into account that the markets are asymmetric. It does matter that the retaliation for deviation happens in a small or in a large market. Therefore, we introduce the second categories of coalitions by using deposit-weighted contact measure. The deposit-weighted contact measure is a sum of weight times the indicator of overlapped market, where the weight is the share of deposits for each region in a given year. If banks i and j are both operating on market 1, then the indicator of overlapped market for banks i and j on market 1 is 1, otherwise it is 0. So the deposit-weighted contact measure, like the absolute contact measure, lies between 0 and 1. Compared with the absolute contact measure, the deposit-weighted contact measure puts more weight on large markets:

$$\lambda_{jk}^{CWI\ n} = \begin{cases} 1, & \text{if } j = k; \\ 1, & \text{if } \sum_{l=1}^{20} \frac{\text{Deposits of region } l}{\text{Deposits of the whole country}} \cdot 1(\text{bank } i \text{ is on market } l) \geq \frac{n}{20}, \\ & \text{ and } \sum_{l=1}^{20} \frac{\text{Deposits of region } l}{\text{Deposits of the whole country}} \cdot 1(\text{bank } j \text{ is on market } l) \geq \frac{n}{20}; \\ 0, & \text{otherwise.} \end{cases}$$

We have also created a mixture of the two; pairwise measure that takes into account the asymmetry of the markets:

$$\lambda_{jk}^{CWII\ n} = \begin{cases} 1, & \text{if } j = k; \\ 1, & \text{if } \sum_{l=1}^{20} \frac{\text{Deposits of region } l}{\text{Deposits of the whole country}} \cdot 1(\text{banks } i \text{ and } j \text{ are on market } l) \geq \frac{n}{20}; \\ 0, & \text{otherwise.} \end{cases}$$

According to the non-nested test, the best models in the first category, or the models that cannot be rejected by other models at 1% significant level, are those coalitions formed by banks with overlapped markets above or equal to 18 or 19, and with 9 or 8 banks involved respectively. The best model in the second category is the coalition formed by banks with the deposit-weighted contact measure equal to 1 and with 6 banks involved. This model is the same as the coalition formed by banks covering at least 20 regions, and is rejected by the coalition formed banks with market coverage of at least 19 regions as in Table 6-A. The best model in the fourth category is the coalition formed by banks with the deposit-weighted coverage measure equal to 1, which is also the same as the coalition formed by banks covering at least 20 regions. In Table 6-B, except the coalition formed by banks covering at least 19 regions and the coalition formed by banks with at least 19 overlapped markets are rejected by the best baseline model (coalition formed by banks with overlapped markets above or equal to 19) at 5% significant level, and all the other models are rejected by the best baseline model at 1% significant level.

Table 7 describes the within group markets shares of banks with at least 19 regions' coverage, the total deposits, HHI (Herfindahl-Hirschman Index) in each market, and the HHI if we treat these banks as one bank. Although there are only 8 banks in the coordination group, their market shares are not small at all. The region level market share of these banks range from 19.7% to 78.3%. The country level "inside market share" of these banks is up to 44.9%. Valle d'Aosta is the region with the greatest share of coalition banks but also with the second highest HHI. However, a large share of the coalition is not related to a large HHI. This highlights the fact that often used HHI index in the bank "competition versus stability" literature may not be a very useful proxy of competitive conduct.

To better describe the characteristics of those banks that form a coalition, we present the summary of own and cross price elasticities estimates in Tables 8 and 9 respectively. In Table 8, the average of local or whole market own-price elasticities of coordinating group are lower than their counterparts of non-colluding group. This means that banks in the coordinating group have greater market power than banks in the non-colluding groups. This is consistent with the observed price level: the average deposit interest rate minus service rate for coordinating group (1.32%) is lower than that for non-colluding group (1.68%) in 2007. In Table 9, the absolute value of the average of local or whole market cross-price elasticities of coordinating group are higher than their counterparts of non-colluding groups and the cross-price elasticities between coordinating and non-colluding groups. This indicates that bank services of non-colluding groups, and bank services between two groups are less substitutable. This is probably because small local banks tend to customize their service more to local markets than large banks. Small banks tend to have their own specific features in tailoring their services to customers, while large banks tend to standardize their service.

5.3 Counter-factual analysis: Consumer welfare

To examine how competition affects consumer welfare we calculate counter-factual measures to compare welfare under the partially collusive and the perfectly competitive scenarios. In each exercise, we solve for a new vector of optimal prices and quantities that satisfy the first order conditions implied by the particular supply model both under the separately and the jointly estimated demand and supply equations. For comparison we also compute the change in consumer welfare through our estimation period of 2003-2007.

The change in welfare per euro:

$$\frac{1}{\alpha}\{\ln[\sum_j \exp(\delta_j^{post})] - \ln[\sum_j \exp(\delta_j^{pre})]\}.$$

The total change in consumer welfare with fixed market size:

$$\frac{1}{\alpha}\{M^{pre}\ln[\sum_j \exp(\delta_j^{post})] - M^{pre}\ln[\sum_j \exp(\delta_j^{pre})]\}.$$

The total change in consumer welfare:

$$\frac{1}{\alpha}\{M^{post}\ln[\sum_j \exp(\delta_j^{post})] - M^{pre}\ln[\sum_j \exp(\delta_j^{pre})]\}.$$

The total social welfare (the total change in consumer welfare plus the total change in banks' profit):

$$\frac{1}{\alpha}\{M^{post}\ln[\sum_j \exp(\delta_j^{post})] - M^{pre}\ln[\sum_j \exp(\delta_j^{pre})]\} + \sum_j(\pi_j^{post} - \pi_j^{pre}),$$

where $-\sum_j(\pi_j^{post} - \pi_j^{pre})$ are banks' excess profits.

Table 10 shows how much change in consumer welfare change per euro and total consumer welfare change from 2003 to 2007 for each region, and total consumer welfare change from 2003 to 2007 for the whole country. The consumer welfare change per euro is positive for 8 regions, while the total consumer welfare change is positive for 16 regions. With fixed market size, the average regional change in total consumer welfare from 2003 to 2007 is 26.9 million of Euros per region, compared to 526 million of Euros when the change in market size is considered. This shows that the increase in total consumer welfare is mainly due to the increase in total market size rather than from the change in bank service, such as interest rate, service rate, and bank coverage. The consumer welfare of the whole country has increased by about 10.5 billion euro from 2003 to 2007 or by 2.63 billion per year.

Table 11 summarizes the counter-factual results for the case where there would be no coalitions in 2007 (competition scenario). If the banking sector were competitive on the deposit services market in 2007, then the average deposit rate minus service rate would increase from 1.65% to 1.78%, and the consumer welfare would have been higher by about $1,769$ million euro. It is equivalent of a 13 basis point difference between the net deposit rates under the two scenarios. This would not be an insignificant amount, when it's gauged to the current low level of interest rates; of course, the interest rate remuneration reflects only in part the full value of deposit services for banks' customers. We also found that the deadweight loss due to the less than competitive banks' behavior amounts to a tangible 1.039 billion euro in 2007.

It would be tempting to draw policy conclusion from our research. However, we recognize that our model does not able to fully describe the complexity of the banking industry. Our paper provides a better approach to measure the competitiveness of the banking sector but we are not able to draw any conclusion on the relationship between competition and systemic stability. The model should be extended to include the loan side of the banking business. We leave these interesting questions for future research.

6 Conclusion

This paper studies the competitive behavior at the Italian retail banking industry, using a structural model of demand and supply side of the deposit market. We find that deposit service demand is moderately price sensitive in Italy. Consumers displayed a stronger preference for higher net deposit interest rates and a well-developed branch systems. In most of our supply specifications we have found that banks that are present at a larger number of regions have better opportunity to lend out their deposit funds at higher interest rates, whereas older banks typically can lend only at lower level or have higher non-interest costs. Our non-nested test could reject the fully collusive model against the competitive model at a 1% significance level. However, we could reject the competitive model and also the fully collusive model against partial collusion of the banks with market contact in at least in 19 regions. Furthermore all other models were rejected by this latter partial collusion model. We found that the loss of depositors' welfare due to the lack of competition was about 1.80 billion euro in 2007.

We conclude with some caveats. First, we have used only the deposit data and banking is naturally a multi-product and multi-sided business. Secondly, our model does not take into account the potential trade-off between competition and stability in the banking system. Finally, our model is static and does not include dynamic considerations, like the choice of the number of branches, or improvements in technological efficiency. To enable us to explore policy implications the model should be extended further to included risks and dynamic elements. We leave these interesting questions for future research.

7 Appendix A

7.1 Results

TABLE 1: Summary Statistics

Variable	Mean	St. Dev.	Min	25%	Median	75%	Max	Obs.
Panel A: Bank characteristics (bank-year level)								
Deposit interest rate	0.0140	0.00725	0.00423	0.0088	0.0114	0.0172	0.0610	517
Service rate	0.00649	0.00725	1.56×10^{-5}	0.0038	0.00557	0.0070	0.0955	517
Deposit interest rate - service rate	0.00750	0.00976	-0.0728	0.0022	0.00603	0.0119	0.0414	517
Number of regions	6.068	5.624	1	2	4	8	20	517
Age	14.23	2.369	1	15	15	15	15	517
Dummy = 1 if age $\geq$ 15	0.880	0.325	0	1	1	1	1	517
Total cost / total assets	0.0207	0.00718	0.00119	0.0171	0.0210	0.0245	0.0549	517
Liquid assets / total assets	0.0748	0.0896	4.94×10^{-5}	0.0192	0.0417	0.0925	0.628	517
Panel B: Bank-market characteristics (bank-region-year level)								
Market share	0.0118	0.0259	6.51e-08	0.000583	0.00259	0.0107	0.319	3118
Within group share	0.0321	0.0592	2.60×10^{-7}	0.00185	0.0080	0.0333	0.502	3118
Number of branches	40.89	80.21	1	3	10	44	1225	3118
Number of competitors with age $\geq$ 15 in the same region	31.81	14.61	8	19	31	49	59	3118
Bad loans / total assets	0.000701	0.00187	0	1.89×10^{-5}	0.000106	0.000487	0.0238	3118
Bad loans / liquid assets	0.0335	0.122	0	0.000255	0.00195	0.0127	1.561	3118
Panel C: Market characteristics (region-year level)								
Number of banks	31.18	14.46	12	20	28.50	39.50	65	100
Total bank deposits (billion Euros)	27	29.6	1.04	7.44	14.5	38.9	140.0	100

Note: If a bank's age is greater than 15, then the age variable is assigned to 15 in the data. Therefore, we introduce an age dummy variable, which is equal to 1 if age $\geq$ 15.

Figure 1: Distribution of Banks' Coverage in 2007

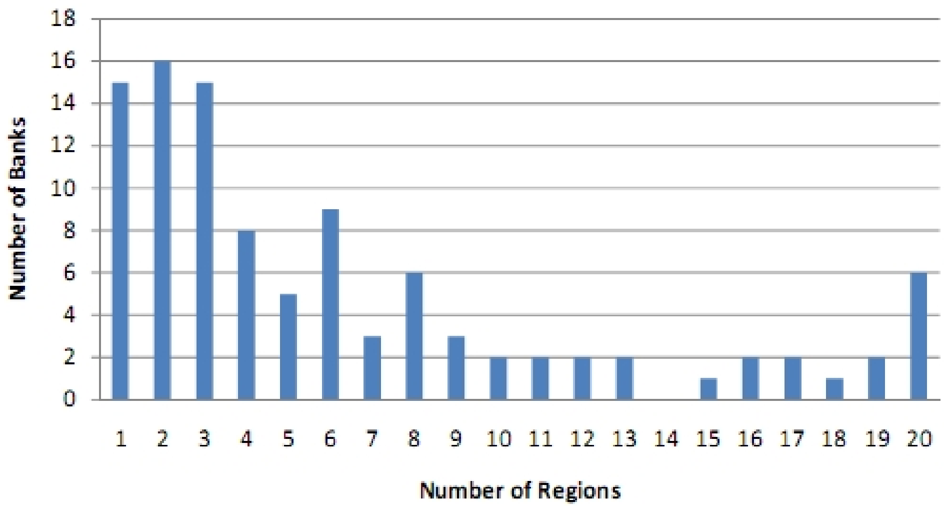

TABLE 2: Demand Estimation: First Stage Regressions

	Dependent variables: ln(within group share)	Dependent variables: Deposit interest rate - service rate	Dependent variables: ln(number of branches)
Explanatory Variables			
Exogenous bank characteristics (bank-region-year level)			
ln(number of regions)	0.448**	-0.000786	0.441***
	(2.37)	(-1.03)	(3.03)
Dummy = 1 if age $\geq$ 15	0.671	-0.00233	0.599
	(0.72)	(-0.92)	(1.11)
Cost characteristics (bank-year level)			
Total cost / total assets	6.270	-0.110	8.221
	(0.16)	(-0.77)	(0.40)
Liquid assets / total assets	2.080	0.0171**	0.0651
	(0.78)	(2.21)	(0.04)
Cost characteristics (bank-region-year level)			
Bad loans / total assets	408.7***	-0.215	354.2***
	(5.03)	(-1.41)	(4.81)
BLP IVs (bank-region-year level)			
ln(sum of the number of regions	-5.422***	0.0119*	-2.187**
of competitors in the same region)	(-3.41)	(1.98)	(-2.02)
Year fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
R^2	0.210	0.407	0.242
F	6.25	25.33	7.07
Markets	20	20	20
Years	5	5	5
Observations	3118	3118	3118

Note: We cluster the standard errors at the bank level.

Numbers in parentheses are t-statistics.

Asterisks indicate significance at 10% (*), 5% (**) and 1% (***) or better.

TABLE 3: Demand Estimation using the Nested Logit models and IV Test Results

Dependent variable: $\ln(s_{jm}) - \ln(s_{0m})$, where s_{jm} is the market share of bank j in market m, and s_{0m} is the market share of outside goods in market m.

First level nest	All banks	All banks	National & local banks	All banks
Second level nest	-	-	-	National & local banks
IVs	No	Yes	Yes	Yes
Explanatory Variables	(i)	(ii)	(iii)	(iv)
Group segmentation parameter	0.997***	0.680***	0.708***	-0.535
(σ_g)	(234.59)	(6.31)	(11.36)	(-0.74)
Subgroup segmentation parameter	-	-	-	0.600***
(σ_{kg})	-	-	-	(4.03)
Deposit interest rate - service rate	0.422	41.19**	39.22***	43.52***
	(0.93)	(2.49)	(3.51)	(3.05)
ln(number of branches)	0.00169	0.383***	0.343***	0.474***
	(0.34)	(3.21)	(5.20)	(2.73)
ln(number of regions)	-0.000137	0.0319	-0.0544***	-0.0971
	(-0.05)	(1.10)	(-2.66)	(-1.43)
Dummy = 1 if age $\geq$ 15	-0.00973	0.0814	0.181*	0.186
	(-1.49)	(0.49)	(1.66)	(1.22)
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
R^2	0.978	0.944	0.943	0.937
F	-	966.4	911.7	880.2
Underidentification test	-	29.74	81.41	10.02
(p value)	-	(0.0000)	(0.0000)	(0.0184)
Hansen J statistic	-	0.098	6.270	3.534
(p value)	-	(0.7544)	(0.0992)	(0.1709)
Markets	20	20	20	20
Years	5	5	5	5
Observations	3118	3118	3118	3118

Note: National banks are defined as banks with market coverage $\geq$ 16.

Market size is defined as total financial assets.

We cluster the standard erros at the bank level.

Demand and supply are estimated separately.

Numbers in parentheses are t-statistics. Asterisks indicate significance at 10% (*), 5% (**) and 1% (***) or better.

TABLE 4: Summary of Elasticities Estimates

Model Numbers in Table 3	(ii)	(iii)
Local market own-price elasticities		
Mean	0.9276	0.9524
25% quantile	0.2078	0.2060
Median	0.6992	0.7078
75% quantile	1.4587	1.5004
Local market cross-price elasticities		
Mean	-0.0168	-0.0330
25% quantile	-0.0123	-0.0273
Median	-0.0024	-0.0050
75% quantile	-0.0003	-0.0006
Whole market own-price elasticities		
Mean	0.9138	0.9214
25% quantile	0.2751	0.2818
Median	0.7150	0.7068
75% quantile	1.4716	1.5025
Whole market cross-price elasticities		
Mean	-0.0058	-0.0113
25% quantile	-0.0026	-0.0051
Median	-0.0001	-0.0003
75% quantile	0.0000	0.0000

Note: Demand and supply are estimated separately.

In the following Tables, the results are based on the demand estimates of Model (ii) in Table 3.

TABLE 5: Supply Estimation

Dependent variable: the recovered deposit return rate

Explanatory Variables	Bertrand	CI 18	CI 19	CII 18	CII 19	Collusion
ln(number of regions)	-0.0006*	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	(-1.8141)	(-1.3137)	(-1.3019)	(-1.3129)	(-1.3024)	(-0.6601)
Dummy = 1 if age $\geq$ 15	-0.0032***	-0.0030***	-0.0031***	-0.0030***	-0.0031***	-0.0036**
	(-4.7132)	(-4.6083)	(-4.7173)	(-4.6199)	(-4.7293)	(-2.1037)
Dummy =1 if it is a national bank	-0.0003	0.0019***	0.0018***	0.0019***	0.0018***	-0.0003
	(-0.5294)	(4.0698)	(3.8635)	(4.0485)	(3.8418)	(-0.2117)
R^2	0.3792	0.4106	0.4064	0.4102	0.4058	0.5139
Deposit return rate	0.0154	0.0162	0.0162	0.0162	0.0162	0.0530
Deposit interest rate - service rate	0.0074	0.0074	0.0074	0.0074	0.0074	0.0074
Markup	0.0080	0.0089	0.0088	0.0089	0.0088	0.0456
Deposit weighted deposit return rate	0.0151	0.0167	0.0167	0.0167	0.0167	0.0557
Deposit weighted (deposit interest rate - service rate)	0.0064	0.0064	0.0064	0.0064	0.0064	0.0064
Deposit weighted markup	0.0086	0.0103	0.0103	0.0103	0.0103	0.0492
Market fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Markets	20	20	20	20	20	20
Years	5	5	5	5	5	5
Observations	3118	3118	3118	3118	3118	3118

Note: Demand and supply are estimated separately.

Numbers in parentheses are t-statistics.

Asterisks indicate significance at 10% (*), 5% (**) and 1% (***) or better.

Markup is defined as Deposit return rate minus (Deposit interest rate - service rate).

National banks are defined as banks with market coverage $\geq$ 16.

We do not list all demand estimates here for space issue.

CI n stands for coalitions that are formed by banks with market coverage at least n.

For example, CI 18 stands for coalitions formed by banks with market coverage at least 18.

CII n stands for coalitions of two banks with at least n overlapped market.

TABLE 6-A:Results of the Rivers and Vuong Test

Test Statistic $T_n = \frac{\sqrt{n}}{\widehat{\sigma_n}}\left(Q_n^1(\widehat{\theta^1}) - Q_n^2(\widehat{\theta^2})\right) \longrightarrow N(0,1)$								
$H_2 \backslash H_1$	Bertrand	CI 15	CI 16	CI 17	CI 18	CI 19	CI 20	Collusion
Bertrand	-	2.2666	4.3474	-5.9975	-5.9991	-5.9893	-6.3072	3.2843
CI 15	-2.2666	-	3.4507	-5.3036	-5.4733	-5.4788	-5.4992	3.2232
CI 16	-4.3474	-3.4507	-	-6.1851	-6.0912	-6.0858	-6.2079	3.1644
CI 17	5.9975	5.3036	6.1851	-	-4.0453	-4.0871	-3.1156	3.4532
CI 18	5.9991	5.4733	6.0912	4.0453	-	-1.9803	3.2392	3.5145
CI 19	5.9893	5.4788	6.0858	4.0871	1.9803	-	3.5481	3.5182
CI 20	6.3072	5.4992	6.2079	3.1156	-3.2392	-3.5481	-	3.4895
Collusion	-3.2843	-3.2232	-3.1644	-3.4532	-3.5145	-3.5182	-3.4895	-

Note: Demand and supply are estimated separately.

Recall that for a (1%) 5% size of the test, H_2 is rejected in favor of H_1 if T_n is lower than the critical value -2.58 (-1.96) and that H_1 is rejected in favor of H_2 if T_n is higher than the critical value 2.58 (1.96).

CI n stands for coalitions that are formed by banks with at least n regions' coverage.

TABLE 6-B: Results of the Rivers and Vuong Test

Test Statistic $T_n = \frac{\sqrt{n}}{\widehat{\sigma_n}}\left(Q_n^1(\widehat{\theta^1}) - Q_n^2(\widehat{\theta^2})\right) \longrightarrow N(0,1)$						
$H_2 \backslash H_1$	Bertrand	CI 18	CI 19	CII 18	CII 19	Collusion
Bertrand	0.0000	-5.9991	-5.9893	-5.9997	-5.9939	3.2843
CI 18	5.9991	0.0000	-1.9803	-1.5944	-1.9880	3.5145
CI 19	5.9893	1.9803	0.0000	1.9699	-0.1005	3.5182
CII 18	5.9997	1.5944	-1.9699	0.0000	-1.9792	3.5148
CII 19	5.9939	1.9879	0.1005	1.9792	0.0000	3.5181
Collusion	-3.2843	-3.5145	-3.5182	-3.5148	-3.5181	0.0000

Note: Demand and supply are estimated separately.

Recall that for a (1%) 5% size of the test, H_2 is rejected in favor of H_1 if T_n is lower than the critical value -2.58 (-1.96) and that H_1 is rejected in favor of H_2 if T_n is higher than the critical value 2.58 (1.96).

CI n stands for coalitions that are formed by banks with at least n regions' coverage.

CII n stands for coalitions of two banks with at least n overlapped market.

TABLE 7: Banks with At Least 19 Regions' Coverage in 2007

Regions	Inside market share	Total deposits (Million of Euros)	HHI	HHI2
Piemonte	0.610	24,824	0.151	0.386
Val d'Aosta	0.783	910.7	0.253	0.631
Lombardy	0.422	53,879	0.103	0.198
Trentino	0.286	1,514	0.177	0.232
Veneto	0.494	18,828	0.104	0.288
Friuli – Venezia	0.487	4,537	0.138	0.311
Liguria	0.425	6,140	0.144	0.268
Emilia – Romagna	0.305	14,625	0.064	0.136
Tuscany	0.352	11,646	0.107	0.190
Umbria	0.605	3,138	0.136	0.401
Marche	0.223	2,450	0.248	0.288
Lazio	0.691	45,011	0.094	0.481
Abruzzo	0.197	1,846	0.098	0.128
Molise	0.491	726.9	0.110	0.287
Campania	0.417	13,870	0.115	0.260
Puglia	0.498	10,432	0.080	0.289
Basilicata	0.317	568.0	0.147	0.230
Calabria	0.572	3,588	0.148	0.421
Sicily	0.394	9,775	0.174	0.301
Sardinia	0.412	4,518	0.280	0.395
Country (mean)	0.449	11,641	0.144	0.306
Country (sum)	-	232,828	-	-

Note: Demand and supply are estimated separately.

HHI2 (Herfindahl index) is computed by treating the coordination group as one bank.

Numbers in parentheses are p-values.

Asterisks indicate significance at 10% (*), 5% (**) and 1% (***) or better.

TABLE 8: Summary of Own Price Elasticities Estimates

Local market own-price elasticities of coordination group	
Mean	0.5578
25% quantile	0.0103
Median	0.2259
75% quantile	0.9986
Local market own-price elasticities of non-coordination group	
Mean	1.0375
25% quantile	0.3063
Median	0.7753
75% quantile	1.5523
Whole market own-price elasticities of coordination group	
Mean	0.5330
25% quantile	-0.0002
Median	0.2093
75% quantile	0.9617
Whole market own-price elasticities of non-coordination group	
Mean	0.9423
25% quantile	0.3130
Median	0.7382
75% quantile	1.5084

Note: Demand and supply are estimated separately.

TABLE 9: Summary of Cross Price Elasticities Estimates

Local market cross-price elasticities within coordination group	
Mean	-0.0288
25% quantile	-0.0321
Median	-0.0072
75% quantile	-0.0002
Local market cross-price elasticities within non-coordination group	
Mean	-0.0135
25% quantile	-0.0092
Median	-0.0019
75% quantile	-0.0003
Local market cross-price elasticities between coordination group and noncoordination group	
Mean	-0.0227
25% quantile	-0.0210
Median	-0.0039
75% quantile	-0.0003
Whole market cross-price elasticities within coordination group	
Mean	-0.0287
25% quantile	-0.0417
Median	-0.0190
75% quantile	-0.0005
Whole market cross-price elasticities within non-coordination group	
Mean	-0.0043
25% quantile	-0.0017
Median	-0.0001
75% quantile	0.0000
Whole market cross-price elasticities between coordination group and noncoordination group	
Mean	-0.0146
25% quantile	-0.0136
Median	-0.0025
75% quantile	-0.0003

Note: Demand and supply are estimated separately.

TABLE 10: Change in Consumer Welfare 2003-2007

Regions	Consumer welfare change per Euro	Total market size in 2003 (Billion of Euros)	Total market size in 2007 (Billion of Euros)	Total consumer welfare change if there is no change in market size (Million of Euros)	Total consumer welfare change (Million of Euros)
Piemonte	-0.0029	101.6	122	-299.2	548.9
Val d'Aosta	-0.0223	2.271	6.61	-50.55	20.33
Lombardy	-0.0073	353.4	510.5	-2586	3655
Trentino	-0.0127	14.44	29.17	-183.2	120.0
Veneto	0.0017	137.0	127.2	230.75	-146.7
Friuli – Venezia	-0.0042	44.65	55.03	-188.1	22.80
Liguria	0.0096	45.74	36.56	441.1	25.57
Emilia – Romagna	-0.0080	135.6	207.8	-1083	1588
Tuscany	0.0069	106.5	88.21	731.0	-92.03
Umbria	0.0029	20.80	20.28	60.72	44.98
Marche	-0.0033	39.54	54.14	-132.5	251.8
Lazio	-0.0233	101.7	234.4	-2370	3160
Abruzzo	0.0152	27.40	18.92	416.0	-29.58
Molise	-0.0153	5.658	14.03	-86.84	29.87
Campania	0.0675	73.72	35.66	4980	647.3
Puglia	-0.0097	51.15	76.73	-495.4	342.53
Basilicata	0.0084	18.96	9.77	159.1	-19.53
Calabria	-0.0062	8.950	10.09	-55.67	6.436
Sicily	0.0297	36.22	28.12	1077	313.0
Sardinia	-0.0014	20.02	21.40	-27.99	33.86
Country (mean)	0.0013	67.27	85.33	26.89	526.1
Country (sum)	-	1,345	1,707	537.8	10,523

Note: Demand and supply are estimated separately.

Total marekt sizes in 2003 have been adjusted to Billion of Euros in 2007 by inflation rate.

TABLE 11: Loss of Consumer Welfare Due To Coalitions Formed by Coalition Relative to Bertrand Competition in 2007

Regions	Consumer welfare loss per Euro	Total market size in 2007 (Billion of Euros)	Total consumer welfare loss (Million of Euros)	Total bank profit change (Million of Euros)	Total welfare loss (Million of Euros)
Piemonte	0.0018	122	216.7	-89.40	127.3
Val d'Aosta	0.0032	6.61	20.99	-4.372	16.62
Lombardy	0.0005	510.5	277.6	-78.66	199.0
Trentino	0.0004	29.17	11.23	-1.745	9.488
Veneto	0.0011	127.2	144.8	-53.22	91.57
Friuli – Venezia	0.0010	55.03	55.18	-10.59	44.59
Liguria	0.0010	36.56	37.96	-14.87	23.10
Emilia – Romagna	0.0003	207.8	70.84	-19.02	51.82
Tuscany	0.0007	88.21	57.73	-19.75	37.98
Umbria	0.0019	20.28	38.39	-11.45	26.94
Marche	0.0003	54.14	15.02	-2.842	12.17
Lazio	0.0021	234.4	501.0	-239.5	261.5
Abruzzo	0.0003	18.92	6.371	-2.023	4.348
Molise	0.0007	14.03	10.34	-1.548	8.794
Campania	0.0019	35.66	67.97	-67.97	0.0037
Puglia	0.0014	76.73	105.1	-31.20	73.90
Basilicata	0.0006	9.77	5.730	-0.8802	4.850
Calabria	0.0042	10.09	42.39	-22.25	20.14
Sicily	0.0019	28.12	53.59	-43.83	9.761
Sardinia	0.0014	21.40	30.03	-14.50	15.53
Country (mean)	0.0013	85.33	88.45	-36.48	51.97
Country (sum)	-	1,707	1,769	-729.6	1,039

Note: Demand and supply are estimated separtely.

8 Appendix B

8.1 Non-nested tests

Here is the procedure for a general non-nested test when a GMM estimation is used. Suppose that for each pairwise comparison there are two models M_1 and M_2. For M_1, the moment conditions that we use are

$$E[m_1(\theta_1)] = 0.$$

For M_2, the moment conditions that we use are

$$E[m_2(\theta_2)] = 0.$$

z is a vector of instruments. There are two requirements for the non-nested test: (1) the GMM estimation has to be overidentified to use the nonnested test; (2) the two comparing models have to share the same instrument variables, z.

Then we use the Rivers and Vuong (2002) test for selection among the firm conducts. The value of the test statistic, $T = \frac{\sqrt{n}}{\widehat{\sigma}}(\widehat{Q_1} - \widehat{Q_2})$, is to be compared with critical values of a $N(0,1)$. $\widehat{Q_1}$ and $\widehat{Q_2}$ are the values of the "first-step" objective functions which employ the same consistent estimator of the weighting matrix W, based on the same set of instruments for the series of models to be compared. W is defined as $W = \frac{1}{n}z'z$, where z is a vector of instruments. $\widehat{Q_i}$ is defined as $\widehat{Q_i} = \widehat{G}_i' W \widehat{G}_i$, where $\widehat{G}_i = \frac{1}{n}\sum m_i(\widehat{\theta}_i)$. $\widehat{\sigma}$ is an estimate of the sampling variance of the difference between objectives and is taken as

$$\sigma^2 = 4[G_1' W E_{11} W G_1 + G_2' W E_{22} W G_2 - 2G_1' W E_{12} W G_2]$$

and is estimated using $\widehat{G}_i = \frac{1}{n}\sum m_i(\widehat{\theta}_i)$ and $\widehat{E}_{ij} = \frac{1}{n}\sum m_i(\widehat{\theta}_i) m_j(\widehat{\theta}_j)'$.

The null hypothesis (H_0) is that M_1 and M_2 are asymptotically equivalent; the first alternative hypothesis (H_1) is that M_1 is asymptotically better than M_2; the second alternative hypothesis (H_2) is that M_2 is asymptotically better than M_1. Let a denote the desired (asymptotic) size of the test and $z_{a/2}$ the value of the inverse standard normal distribution function evaluated at $1 - a/2$. If $T_n < -z_{a/2}$, we reject H_0 in favor of H_1; if $T_n > z_{a/2}$, we reject H_0 in favor of H_2; Otherwise, we accept H_0.

There are two estimation approaches. The first estimation approach is to estimate the demand and supply sides in sequence. The second estimation approach to estimate them jointly. Correspondingly there are also two ways to conduct the non-nested test.

8.1.1 A non-nested test on the supply side

If we estimate the demand side and the supply side in sequence, then for the nonnested test we only use the moment conditions on the supply side as follows:

$$E[m(\theta)] = E[z^{s\prime}(\widehat{r} - x^s \gamma^s)] = 0,$$

where

z^s is a vector of supply instruments,

$\widehat{r}$ is the recovered deposit return rate,

x^s is a vector of independent variables for costs, and

γ^s is a vector of cost parameters to be estimated.

The recovered deposit return rate, $\widehat{r}$, is a function of the estimates of price coefficient, $\widehat{\alpha}$ and the estimate of the nested logit parameter, $\widehat{\sigma}$. Both $\widehat{\alpha}$ and $\widehat{\sigma}$ are estimated from the demand estimation, and are treated as known variables in the nonnested test. So $\widehat{r}$ are also known in the nonnested test.

Recall that the deposit return rate is specified as $r_j = \gamma_0 + \gamma_r \ln(regions_j) + \gamma_a \ln(age_j) + \omega_{jm}$. So $x^s = (1, \ln(regions_j), \ln(age_j))$ and $\gamma^s = (\gamma_0, \gamma_r, \gamma_a)$.

The weighting matrix W is computed only from the supply instrument z^s. That is to say, $W = \frac{1}{n} z^{s\prime} z^s$.

Suppose that we want to choose between two models: M_1 and M_2. The moment conditions are

$$\begin{aligned} m_1(\widehat{\theta_1}) &= z^{s\prime}(\widehat{r_1} - x^s \widehat{\gamma_1^s}), \\ m_2(\widehat{\theta_2}) &= z^{s\prime}(\widehat{r_2} - x^s \widehat{\gamma_2^s}) \end{aligned}$$

where

$\widehat{r_1}$ is the recovered deposit return rate from models M_1,

$\widehat{r_2}$ is the recovered deposit return rate from models M_2,

$\widehat{\gamma_1^s}$ and $\widehat{\gamma_2^s}$ are the estimates of the supply parameters from models M_1 and M_2 respectively.

Then we can compute the nonnested test statistics, T_n.

If $T_n < -z_{a/2}$, then we conclude that M_1 is asymptotically better than M_2 at significant level a.

If $T_n > z_{a/2}$, then we conclude that M_2 is asymptotically better than M_1 at significant level a.

Otherwise, we conclude that M_1 and M_2 are asymptotically equivalent at significant level a.

8.1.2 A non-nested test on both the demand and supply sides

If we estimate the demand side and the supply side jointly, then for the non-nested test we use both the moment conditions on the demand and supply sides as follows:

$$E[m(\theta)] = E\begin{bmatrix} z^{d\prime}(\delta - x^d\gamma^d) \\ z^{s\prime}(r - x^s\gamma^s) \end{bmatrix} = 0,$$

where

z^d is a vector of demand instruments,

δ is a vector of the mean utility,

x^d is a vector of observed product characteristic variables without random coefficients, and

γ^d is a vector of cost parameters to be estimated.

In the nested logit model, the mean utility can be computed directly from $\delta_j = \ln(s_j) - \ln(s_0) - \sigma\ln(s_{j/g}) - \alpha p_j$ and $x^d = (1, x)$. Or we can compute the mean utility from $\delta_j = \ln(s_j) - \ln(s_0) - \sigma\ln(s_{j/g})$ with $x^d = (1, p, x)$.

We can rewrite the moment conditions as

$$E[m(\theta)] = E[Z'(Y - X\gamma)] = 0,$$

where

$$Y = \begin{pmatrix} \delta_1 \\ r_1 \\ \vdots \\ \delta_n \\ r_n \end{pmatrix},\ X = \begin{pmatrix} x_1^d & 0 \\ 0 & x_1^s \\ \vdots & \vdots \\ x_n^d & 0 \\ 0 & x_n^s \end{pmatrix},\ Z = \begin{pmatrix} z_1^d & 0 \\ 0 & z_1^s \\ \vdots & \vdots \\ z_n & 0 \\ 0 & z_n^s \end{pmatrix},$$

$$\gamma = \begin{pmatrix} \gamma^d \\ \gamma^s \end{pmatrix}, \text{ and } \theta = (\gamma, \alpha, \sigma).$$

γ is a vector of all linear parameters. δ is a function (numerical) of price coefficient, α, and the nested logit parameter, σ. r is a function of α and σ. So Y is a function of α and σ. The parameters of the whole model, θ, should include γ, α and σ.

For each pairwise comparison, there are two competing models, M_1 and M_2. The moment conditions are

$$\begin{aligned} m_1(\widehat{\theta}_1) &= Z'(Y_1 - X\widehat{\gamma}_1), \\ m_2(\widehat{\theta}_2) &= Z'(Y_2 - X\widehat{\gamma}_2) \end{aligned}$$

where

$$Y_1(\widehat{\alpha_1}, \widehat{\sigma}_1) = \begin{pmatrix} \widehat{\delta}_1 \\ \widehat{r}_1 \\ \vdots \\ \widehat{\delta}_n \\ \widehat{r}_n \end{pmatrix}_1, \ Y_2(\widehat{\alpha_2}, \widehat{\sigma}_2) = \begin{pmatrix} \widehat{\delta}_1 \\ \widehat{r}_1 \\ \vdots \\ \widehat{\delta}_n \\ \widehat{r}_n \end{pmatrix}_2,$$

Y_1 is a vector of the estimated mean utility and the recovered deposit return rate from model M_1,

Y_2 is a vector of the estimated mean utility and the recovered deposit return rate from model M_2,

$\widehat{\gamma}$ is a vector of the estimates of all demand and supply parameters except the estimate of price coefficient, $\widehat{\alpha}$, and the estimate of the nested logit parameter, $\widehat{\sigma}$, and

$\widehat{\theta} = (\widehat{\gamma}, \widehat{\alpha}, \widehat{\sigma})$ is a vector of all parameters in the model.

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